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Breast Cancer Diagnosis based on Frequency Converters and Extraction of Effective Features

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ABSTRACT

Solar Breast cancer is the most common type of cancer among women. Early diagnosis of this disease and its treatment can significantly reduce the death rate from this cancer. The separation of benign and malignant masses in mammography images is one of the important factors in the timely detection of breast cancer, which in some cases, due to the density and natural structure of the breast, deep and hidden disorders, make the diagnosis difficult for radiologists. In this study, frequency transformations and Naive Bayes classification have been used to extract effective features in mammography images. The presented method aims to increase the accuracy of diagnosis between malignant and benign tumours in mammography images. The results obtained from the implementation of the proposed method on the MIAS database show that the proposed method was able to improve the accuracy of diagnosing this disease on normal and abnormal images by 91%, Precision by 98%, Recall by 987%, and F-measure by 90%.

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Introduction

Breast cancer is one of the most common cancers among women and one of the main causes of their deaths, which can be drastically reduced if diagnosed quickly and properly [1]. In the United States, one out of every eight women who live to the age of 95 will get this cancer [2]. This cancer is one of the most common cancers diagnosed among women, and death as a result occurs in mostly women between the ages of 15 and 54 [3]. A few of the main factors such as family history are known to increase the incidence of breast cancer in women [4]. A large number of women who get breast cancer do not have any history of the disease in their family. This type of cancer cannot be prevented because the main reasons for its occurrence are not yet known, but its timely diagnosis can increase the chance of a person's full recovery [5]. Therefore, early detection of breast cancer is one of the most important factors in determining the stages of treatment for women with malignant tumours [6]. The most important method in breast cancer diagnosis is mammography. Unfortunately, mammography sometimes performs poorly in distinguishing between benign and malignant masses [7]. Today, computer-aided diagnosis (CAD) systems are designed and used to help radiologists and doctors with early cancer diagnosis [8]. In recent years, a great deal of research has been carried out on mammography images, so that cancerous masses can be diagnosed without the intervention of the diagnostician using image processing methods and computer programs [9]. However, identifying breast cancer in the early stages can play an important role in reducing disease and mortality rates. In the diagnosis of breast cancer based on mammography images, there are shortcomings such as imaging noise, low accuracy during imaging as well as microscopic patterns of cancer, leading to problems in identifying this cancer [10]. In the previous methods of cancer diagnosis, there were uncertain boundaries between classes where the errors of most classification algorithms occur in these parts [11]. By limiting these boundaries, it is possible to increase the detection rate of breast cancer [12]. Timely diagnosis of breast cancer increases the patient's survival chances, so the presence of an accurate and reliable system for the timely diagnosis of benign or malignant breast tumors seems essential [13]. This study aimed to investigate flexible tools for early detection of breast cancer in mammography images. Considering the examination of the problem of breast cancer diagnosis and the explanation of the challenges related to increasing the detection accuracy, in this study, a proposed approach for breast cancer detection is presented to increase the detection accuracy for normal/abnormal and benign/malignant classes. To solve this problem, a method for breast cancer detection using frequency transformations for extracting effective features and

Naive Bayes classification was presented. The main objective of the proposed approach was to predict cancer samples and steps related to identification with high accuracy. Some of these important goals included: (1) Breast cancer detection in mammography images with a combined method based on feature extraction; (2) Increasing the accuracy of classification and diagnosis for normal/abnormal and benign/malignant classes; (3) Increasing the percentage of accuracy tumor isolation. The structure of this article is as follows: in the second part, an overview of different techniques and methods in breast cancer diagnosis related to recent years is discussed. In the third part, the proposed method is discussed using the presentation of important frequency transformations to extract the effective features. In the fourth part, the results obtained from the proposed method are presented. Conclusions and future suggestions are also presented in the fifth section.

Related works

This section reviews recent studies conducted in the field of breast cancer detection. According to the results obtained in all the methods, the MIAS dataset [14] images and the LOOCV [6] validation techniques were considered.

In [15], an algorithm called CNNI-BCC[1] was proposed for breast cancer classification. CNNI-BCC uses a CNN to improve breast cancer lesion classification and assist medical professionals in breast cancer detection. The proposed method aimed to assist medical professionals in breast cancer lesion classification by executing a CNN for breast cancer classification. Experimental results showed that the proposed method achieved an average accuracy of 90.50% on the MIAS dataset. The proposed method uses a convolutional neural network to improve the classification of breast cancer lesions to help experts in breast cancer diagnosis. In 2018, a deep convolutional neural network based on CAD systems was used to assist radiologists in classifying mammographic masses. Deep learning typically requires large datasets to train networks of a certain depth from scratch. Transfer learning is an effective method for dealing with relatively small datasets. In this study, after preprocessing and normalizing all Regions of Interest (RoIs) extracted from full mammograms, all dataset images were used to create a large dataset using data augmentation techniques and image fusion. Experimental results showed that the proposed method achieved an average accuracy of 67.96% on the INbreast dataset. In the PCA-CC method [16] and the proposed method, the dimensions of the images of the extracted area of interest were 200 x 200 pixels, whereas they were 128 * 128 pixels for other methods. In the COCC method [17], the classification method used was the simple

[1] Convolutional Neural Network Improvement for Breast Cancer Classification

logistic classification, which is considered for the SCC and PCA-CC [18] support vector machine (SVM) methods and for the proposed Naive Bayes method. The number of images used for each of the methods is different; it is 330 mammography images for the proposed method and 300, 307, 200, and 305 for the CNNI-BCC, SCC, PCA-CC, and COCC methods, respectively.

Proposed method

In this section, the proposed method for detecting breast cancer in mammography images based on frequency transformations and Naive Bayes classification [15] is discussed. The Naive Bayes classifier is a supervised machine learning algorithm that is used for classification tasks such as text classification. They use principles of probability to perform classification tasks. The generality of the proposed method is that after loading the mammography images from the database, the interested areas are extracted from the images, and then Fourier and cosine frequency transformations are applied to the extracted areas. In the next stage of the work, the features (μ, M, K, S) are extracted for the coefficients resulting from the transformations and the desired image itself; the extracted features are included in a table called the feature table. Finally, according to the created table and using the Naive Bayes technique, the accuracy of the classifier is calculated by considering different evaluation criteria. In the proposed method, 330 mammography images from the MIAS dataset were considered. In addition to mammography images, information for each image was available in the database. This information for each image included items that indicated whether the image in question was normal or not (a mass was present or not). If the image is abnormal, whether it is benign or malignant, as well as its exact location is specified in the image. The area of interest is extracted from the middle of the image (with dimensions of 200*200 pixels) if the input image from the database is normal, but if the input image is abnormal, it is extracted based on the information in the database, where the mass is located in the image and a piece from that location with dimensions of 200 * 200 pixels. Therefore, for each natural or unnatural image, a piece of 200 * 200 pixels is extracted. The images in the database become images with dimensions of 200 * 200 pixels. It should be considered that the dimensions of the main images in the database were 512 * 512 pixels. Figure 1 shows an example of mammography images with dimensions of 200 * 200 pixels extracted from the original image.

Figure 1. Examples of images extracted from the database that were converted into 200*200 pieces. Right Image (Normal Image) / Left Image (Abnormal Image) [19]

After obtaining the region of interest from the original image, Fourier and cosine transforms were applied to each image of the region of interest. In the next step, for the coefficients obtained by Fourier and cosine transformation and the image of the area of interest, the characteristics of M_p, μ_p, K, S were calculated. The total number of features was obtained by considering all the coefficients and the image of the area of interest; 30 features were obtained for each image and 30 features were calculated for each image.

The calculation of M_p is shown in Equation (1) where X=(X_i)_(1≤i≤N) is a distribution of N transformation coefficients.

$$M_p = \frac{1}{N}\sum_{i=1}^{N}(X_i)^p \qquad p = 1, 2, 3, 4 \tag{1}$$

The calculation of μ_p is shown in Equation (2) where the mean of μ_p represents the estimate of the place where the center of clustering occurs and is equal to the first moment.

$$\mu_p = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^p \qquad p = 1, 2, 3\ 4 \tag{2}$$

The calculation of K in Equation (3) shows that Kurtosis measures the relative elongation coefficient or the smoothness of the distribution for one normally.

$$kurtosis = \frac{\mu_4}{(\mu_2)^2} - 3 \tag{3}$$

The calculation of S is shown in Equation (4) where Skewness indicates the degree of distribution asymmetry.

$$skewness = \frac{\mu_3}{(\mu_2)^{3/2}} \quad (4)$$

Based on the obtained features, a feature table containing 330 rows (the number of images in the database) and 30 columns (related to the extracted features for each image) was created. In the next step, a logarithm in base 10 was taken from the table of desired properties because the scale of the features was different (feature values between -∞,+∞). For this reason, the attribute values were equalised using the logarithm in bases of 10, and the attribute range was considered between -50 and +50. In the next step, all the values in the attribute table were rounded. The final attribute table was obtained by performing the above steps. Finally, a column called the target column was added (certainty of the class type). An example of the calculation of the target is shown in Table 1 to carry out the classification step.

Table 1. An example of features created in the proposed method.

Figure Feature	1	2	3	Normal/ Abnormal
Figure 1	50	-	-	0
Figure 2	20	-	-	1
Figure 3	10	-	-	1
Figure 4	60	-	-	0
Figure 5	30	-	-	1

The LOOVC [6] method was used to obtain classification accuracy. The LOOVC method is a model evaluation method that determines the extent to which the results of a statistical analysis on a data set are generalizable and independent of the training data. This method is especially used in forecasting applications to determine how useful the desired model will be in practice. The LOOVC method in the proposed method was performed in such a way that, for example, if image 1 of Table 1 was not available in the table, would it be better to perform the classification or not? In other words, it is assumed that image 1, which is known to be normal or abnormal, is removed from Table 1, and the desired image is applied as the input of the classification. The Naive Bayes classifier determines which class the input image belongs to by considering Table 1. Therefore, considering the Naive Bayes equation it is assumed that the number of features of the input image is 4 (Figure 3). Furthermore, the features table should contain 11 rows and 4 columns in addition to the target column (with benign/malignant class) (Figure 2).

Input Image Features

3	1	3	3

Feature Table

X_1	X_2	X_3	X_4	T
1	2	3	3	0
3	2	3	1	0
3	2	1	3	1
2	2	1	3	1
3	1	2	3	0
2	2	3	3	1
2	1	3	3	0
3	2	3	3	1
2	3	2	1	1
1	2	3	1	1
1	3	2	1	1

Figure 2. An example of 4 features extracted from the input image in addition to the feature table obtained.

Equation (5) was used to determine which case (benign or malignant) the input image belongs to.

$$P(T=t|X_1,X_2,X_3,X_4)=\frac{P(T=t)\Pi P(X_i|T=t)}{\sum_j^{0,1}P(T=t_j)\Pi P(X_i|T=t_j)} \tag{5}$$

According to the above equation, the number of X is equal to the number of features. The T value is equal to zero or one (a value of zero equals benign and a value of 1 equals malignant). First, the desired equation is considered as T=0 and T=1 again. It is assumed that if the value of T=0, X_i |T=t┤ indicates that the input features have been repeated several times considering T=0 in the feature table. Moreover, the value of P(T=t) is the number of T=0 in the attribute table. Therefore, Equation (6) was used to determine whether the input image was benign or malignant.

$$\begin{gathered}\mathrm{P}(\mathrm{T}=0|3\quad 1\quad 3\quad 3)=\frac{\frac{4}{11}\left(\frac{2}{4}\times\frac{2}{4}\times\frac{3}{4}\times\frac{3}{4}\right)}{\frac{4}{11}\left(\frac{2}{4}\times\frac{2}{4}\times\frac{3}{4}\times\frac{3}{4}\right)+\left(\frac{7}{11}\middle|\frac{2}{7}\times 0\times\frac{3}{7}\times\frac{3}{7}\right)}=1\\ \mathrm{P}(\mathrm{T}=1|3\quad 1\quad 3\quad 3)=\frac{0}{0+\left(\frac{4}{11}\middle|\frac{2}{4}\times\frac{2}{4}\times\frac{3}{4}\times\frac{3}{4}\right)}=0\end{gathered} \tag{6}$$

Thus, according to the output of the classifier, the value is 1 for T=0; the input image is of the benign type. By also examining the initial input image whose T value was already known (its benign and malignant type) and the output of the classifier whose type was benign, a positive score was considered if the T of the initial image was zero, otherwise, a negative score was recorded. According to the stated contents for all the available images (330 images), 330 points (positive or negative) were obtained, the evaluation criteria checked and classification accuracy for normal/abnormal and benign/malignant classes determined.

Experimental results

In this section, the results of the proposed method are studied and evaluated. The proposed method was implemented with the help of MATLAB software, version 2019. In the obtained results, the detection accuracy in the breast cancer training dataset was 91% for the normal/abnormal class and 86% for the benign/malignant class, which indicates the high efficiency of the proposed method. Compared to other breast cancer detection methods, there is a significant improvement in the three parameters of accuracy, sensitivity, and specificity. To implement the proposed method, the set of mammography images from the MIAS dataset was used. To evaluate the presented method, the desired method was implemented many times to determine the accuracy level in the detection of samples at each stage. Figure 3 shows some examples of regions of interest from the MIAS dataset used in the implementation. These areas of interest belong to different types and severity of pathologies. As stated in the proposed method, the dimensions of these samples were 200*200 pixels, which were extracted from mammography images in the database, and by extracting these pieces, the proposed method was performed by applying frequency transformations and Naive Bayes classification.

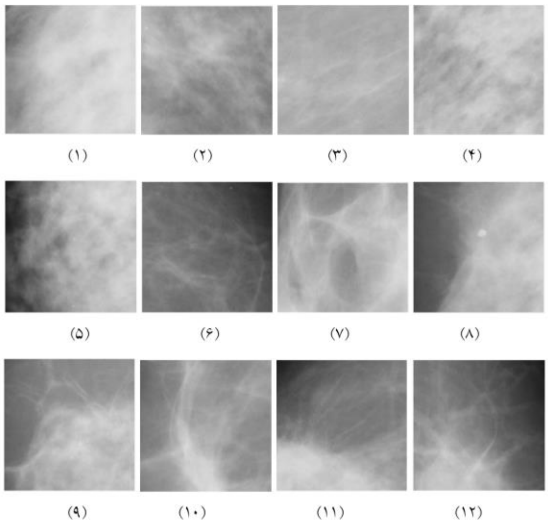

Figure 3: An example of regions of interest used from the MIAS dataset.

The accuracy of a particular test in the field of breast cancer detection was expressed using three main indicators accuracy, sensitivity, and specificity. Accuracy, sensitivity, specificity, Precision or PPV, and NPV indices were used to evaluate the proposed method after implementation [6].

The evaluation criterion used to measure the accuracy of the proposed model in the present research was the correct matching rate of blood vessel patterns in retinal images in the stages of model training on three sets of training, validation, and testing images. For this purpose, a confusion matrix was drawn, in which the number of correctly matched images versus wrongly matched images in the training, validation, and data testing stages was determined. This matrix contained four true positive (TP), false positive (FP), true negative (TN) and false negative (FN) elements, as follows in the proposed method.

- ***TP:*** The patterns of test images and training images are the same and the model has correctly recognized the same.
- ***TN:*** The patterns of the test I mages and the training images are the same and the model has incorrectly detected a mismatch.
- ***FP:*** The patterns of the test and training images are not the same, and the model has correctly detected the mismatch.
- ***FN:*** The patterns of the test and training images are not the same, and the model has mistakenly recognized the same.

The most important criteria are Accuracy, Precision, Recall, Sensitivity, and F-measure criterion. These criteria are defined based on the following relationships. Accuracy is the number of correctly classified samples, compared to the total samples. Sensitivity is also called true positive rate or probability of correct detection in some sciences. It is the proportion of positive cases that the test correctly marks as positive. For instance, the percentage of sick people who are correctly identified and these people are not healthy. Specificity is also called true negative rate which refers to the proportion of negative cases that the test correctly flags as negative. For example, the percentage of healthy people who were correctly identified and these people were not sick. The evaluation criteria for normal/abnormal and benign/malignant classes were calculated as shown below:

$$\text{Accuracy} = \frac{\text{TP + TN}}{\text{TP+TN+FP+FN}} \tag{7}$$

$$Sensivity = \frac{TP}{TP\ +\ FN} \tag{8}$$

$$Specificity\ = \frac{TN}{FP\ +\ TN} \tag{9}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{10}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{11}$$

$$\text{F} - \text{measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{12}$$

Table 2 shows the evaluation criteria values of normal/abnormal (N/A) and benign/malignant (M/B) classes for the proposed method. The obtained values show the high accuracy of the proposed method. According to the results, the accuracy value of normal/abnormal is greater than benign/malignant.

Table 2. Evaluation Criteria values for normal/abnormal and benign/malignant classes by the proposed method.

Class	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F-measure (%)
Normal/Abnormal	91	75	99	98	87	90
Benign/Malignant	86	96	43	87	76	85

Figure 4 shows the results related to the evaluation criteria for normal/abnormal and benign/malignant classes. According to the obtained results, it can be observed that the proposed method for classifying the normal/abnormal class performed better than the benign/malignant class. The accuracy criterion for the normal/abnormal class was 91%, and this value for the benign/malignant class was 86%. Figure 4 shows the comparison of the values of evaluation criteria for N/A and N/B classes in a diagram. According to the stated content, it can be concluded that the proposed method was capable of meeting the goals of increasing the accuracy of classification and diagnosis for normal/abnormal and benign/malignant classes.

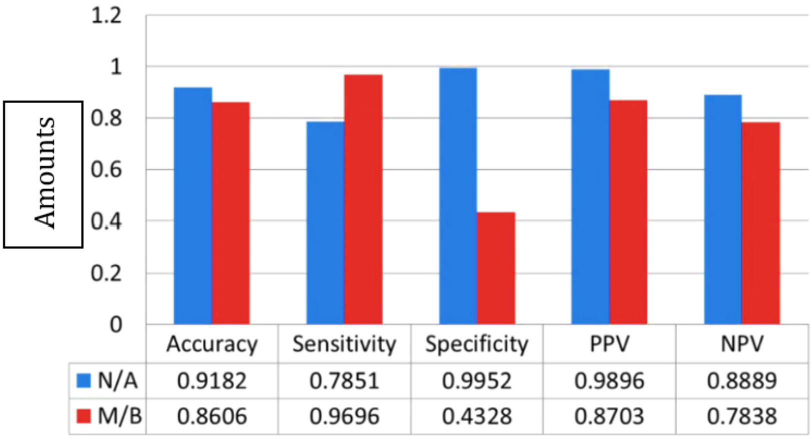

Figure 4. Comparison of evaluation criteria values for N/A and M/B classes by the proposed method.

Tables 3 and 4 illustrate the performance comparison of the proposed method to identify normal/abnormal and benign/malignant classes with other methods examined in the second part. Taking into consideration the mentioned cases, the results demonstrated the high accuracy of the proposed method for diagnosis for both normal/abnormal and benign/malignant classes compared to other methods. In the proposed method with the feature set size of 30, the accuracy obtained was 91%.

Table 3. Comparing the accuracy of the proposed method for distinguishing natural/unnatural classes with other methods.

Method	Classification	The size of the area of interest	Number of images	Accuracy (%)
CNNI-BCC **[15]**	NB	200*200	300	90
SCC **[16]**	SVM	128*128	307	85
PCA-CC **[17]**	SVM	200*200	200	90
COCC **[18]**	Simple logistics	128*128	305	83
# The Proposed Method	NB	200*200	330	91

Table 4. Comparing the accuracy of the proposed method to distinguish benign/malignant classes with other methods.

Method	Classification	The size of the area of interest	Number of images	Accuracy (%)
CNNI-BCC **[15]**	NB	200*200	300	89
SCC **[16]**	SVM	128*128	400	69
PCA-CC **[17]**	SVM	200*200	1024	72

COCC **[18]**	Simple logistics	128*128	1056	75
# The Proposed Method	NB	200*200	80	86

Conclusion and future works

Breast cancer is the most common cancer among women and is considered the second cause of death in women. Published statistics show that this type of cancer is increasing in developed and developing countries. In this type of cancer, it is difficult for the doctor to diagnose whether this disease is benign or malignant. The presence of a lump of fat on the chest is a warning sign of this disease. However, this symptom is not always a sign of a malignant and dangerous cancer. The method of sampling breast fat with the help of a thin needle is one of the effective and non-injury methods, which is considered a suitable test for breast cancer diagnosis and provides the information needed to evaluate whether the disease is benign or malignant. In this study, frequency transformations and Naive Bayes classification were used to detect breast cancer in mammography images. First, in the proposed method, the region of interest was extracted from mammography images, then frequency transformations were applied to the region of interest, and in the next step, features were extracted, and breast cancer was identified by creating a feature table using the Naive Bayes classifier. The proposed method was implemented considering the set of mammography images from the MIAS database and MATLAB software. The results of the implementation show a high classification accuracy for the normal/normal (91%) and benign/malignant (86%) classes compared to other methods. Furthermore, by comparing the proposed method with similar methods, it can be concluded that by applying frequency transformations, Naive Bayes classifier, and by obtaining effective features, breast cancer can be diagnosed with appropriate accuracy. Based on access to the desired data the topicality of the issue, the presentation of various solutions on sites and extensive research in different countries to achieve the best diagnosis process, it can collect the research conducted in different countries and evaluate their success rate. However, in the near future, digital mammography archives will require much effort to reduce costs. The digital mammography image also offers new ways to optimize the image that might lead to a better understanding of lesion growth. In addition, the introduction of digital mammography leads to new ways to design screen strategies for mammography screening, and with the progress of different fields in mammography, it is hoped that new methods will be provided for diagnosing cancerous masses with the least time and cost. Therefore, despite the significant progress that has been made in the last twenty years, more work is still required to expand cancer detection systems with computerized systems and the use of accurate methods. The use of an efficient and effective method should lead to the early detection of breast cancer and an advanced prognosis of the disease.

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